MIPT Data Visualization Course

Data Visualization in Modern Machine Learning

Ashuha Arseniy[1,2]

Bayesian Research Group[1], MIPT[2]

ars-ashuha.ru/slides

November 17, 2016

Motivation

Motivation

Motivation

Motivation

Motivation

- It's a little bit sad, but we can plot only 2D data, isn't it?

Motivation

Motivation

- It's a little bit sad, but we can plot only 2D data, isn't it?
- A goal of data visualization is to understand inner data structure.

Motivation

Motivation

- It's a little bit sad, but we can plot only 2D data, isn't it?
- A goal of data visualization is to understand inner data structure.
- Or represent data in a much more interpretable form.

Motivation

Motivation

- It's a little bit sad, but we can plot only 2D data, isn't it?
- A goal of data visualization is to understand inner data structure.
- Or represent data in a much more interpretable form.

There are two way to get this goal:

Motivation

Motivation

- It's a little bit sad, but we can plot only 2D data, isn't it?
- A goal of data visualization is to understand inner data structure.
- Or represent data in a much more interpretable form.

There are two way to get this goal:

- Low Rank Way (SVD, Auto-encoders, LDA, etc.)

Motivation

Motivation

- It's a little bit sad, but we can plot only 2D data, isn't it?
- A goal of data visualization is to understand inner data structure.
- Or represent data in a much more interpretable form.

There are two way to get this goal:

- Low Rank Way (SVD, Auto-encoders, LDA, etc.)
- Generative Models Way (GAN, Image Capturing, etc.)

Low Rank idea

Low Rank idea

- We have matrix $X_{items \times features}$

Low Rank idea

- We have matrix $X_{items \times features}$
- Let's try to represent each item's vector as smaller ones.

Low Rank idea

- We have matrix $X_{items \times features}$
- Let's try to represent each item's vector as smaller ones.
- What should we do?

Low Rank idea

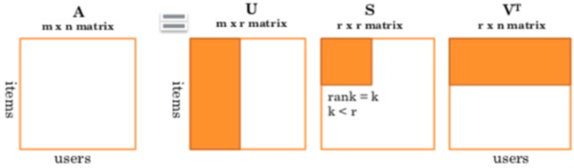
- We have matrix $X_{items \times features}$
- Let's try to represent each item's vector as smaller ones.
- What should we do?

Principal component analysis is a matrix decomposition

Low Rank idea

- We have matrix $X_{items \times features}$
- Let's try to represent each item's vector as smaller ones.
- What should we do?

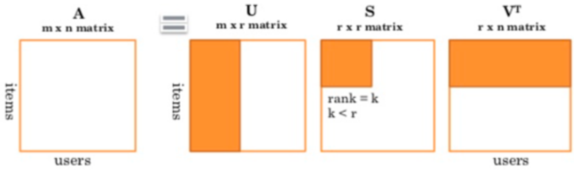
Principal component analysis is a matrix decomposition



Low Rank idea

- We have matrix $X_{items \times features}$
- Let's try to represent each item's vector as smaller ones.
- What should we do?

Principal component analysis is a matrix decomposition

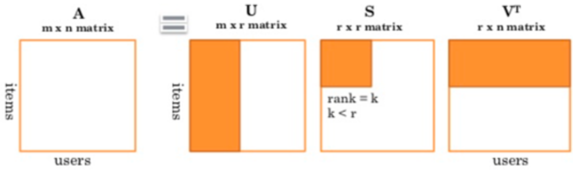


Intuition save maximum data variance, minimize L_2 norm

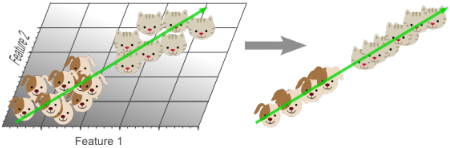
Low Rank idea

- We have matrix $X_{items \times features}$
- Let's try to represent each item's vector as smaller ones.
- What should we do?

Principal component analysis is a matrix decomposition



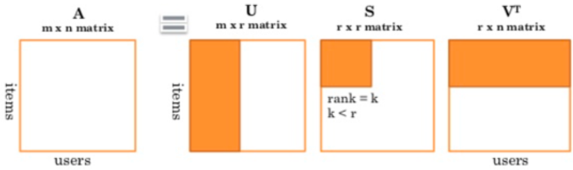
Intuition save maximum data variance, minimize L_2 norm



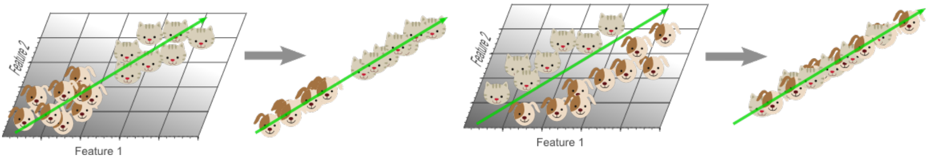
Low Rank idea

- We have matrix $X_{items \times features}$
- Let's try to represent each item's vector as smaller ones.
- What should we do?

Principal component analysis is a matrix decomposition



Intuition save maximum data variance, minimize L_2 norm



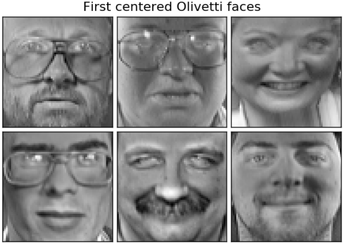
SVD: Faces dataset

SVD: Faces dataset

Main components:

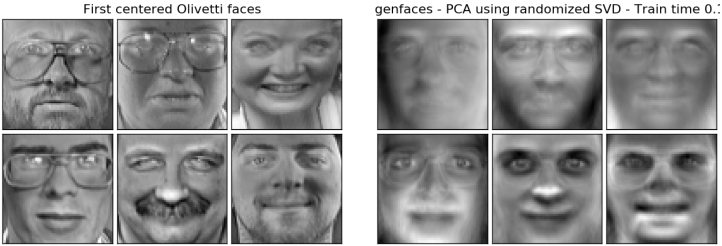
SVD: Faces dataset

Main components:



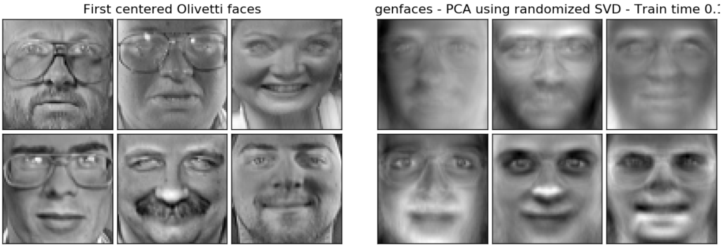
SVD: Faces dataset

Main components:



SVD: Faces dataset

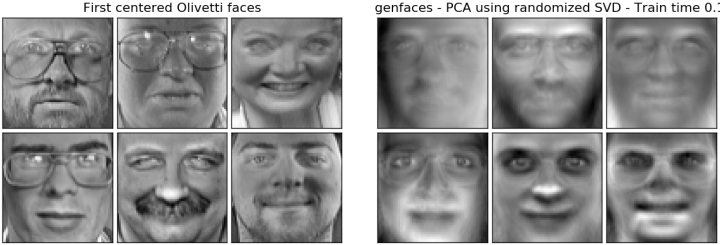
Main components:



Plot in 2d:

SVD: Faces dataset

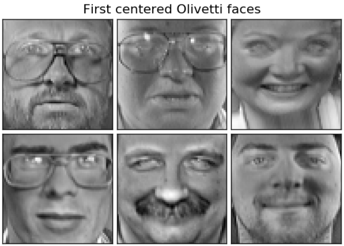
Main components:

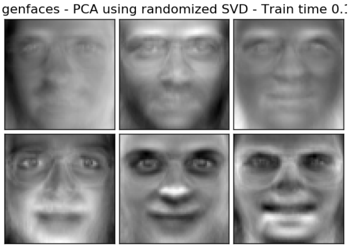


Plot in 2d:

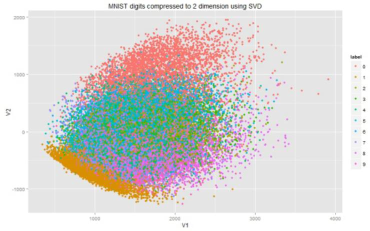
SVD: Faces dataset

Main components:





Plot in 2d:



Non-linear generalization

Non-linear generalization

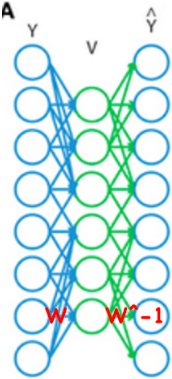
- What did we do wrong? Our picture mixes different classes and so on.

Non-linear generalization

- What did we do wrong? Our picture mixes different classes and so on.
- Let's try nonlinear generalization.

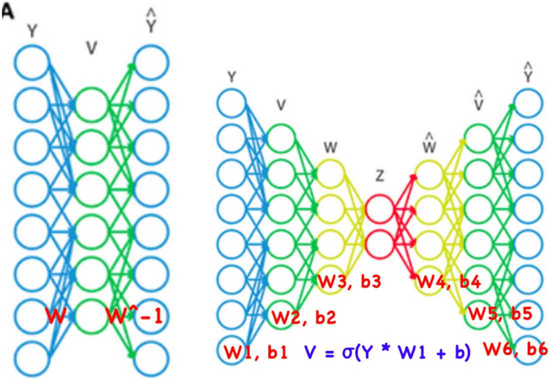
Non-linear generalization

- What did we do wrong? Our picture mixes different classes and so on.
- Let's try nonlinear generalization.



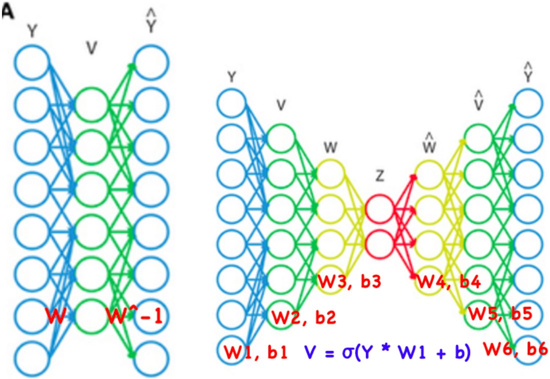
Non-linear generalization

- What did we do wrong? Our picture mixes different classes and so on.
- Let's try nonlinear generalization.



Non-linear generalization

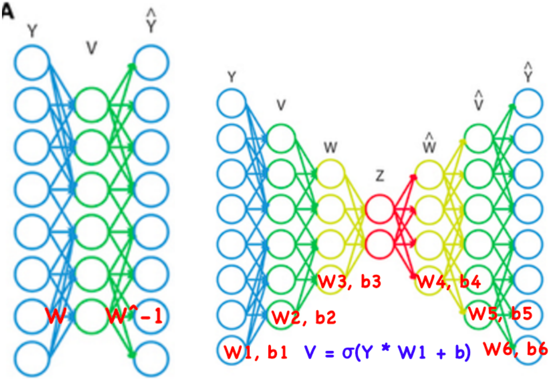
- What did we do wrong? Our picture mixes different classes and so on.
- Let's try nonlinear generalization.



- How to find W_n, b_n?

Non-linear generalization

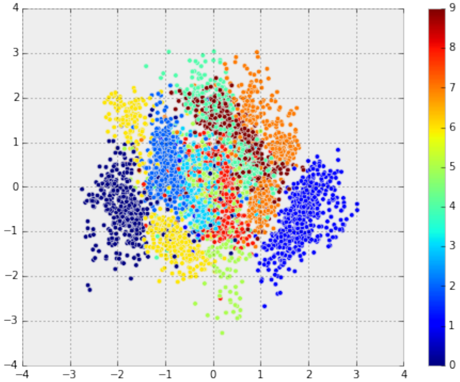
- What did we do wrong? Our picture mixes different classes and so on.
- Let's try nonlinear generalization.



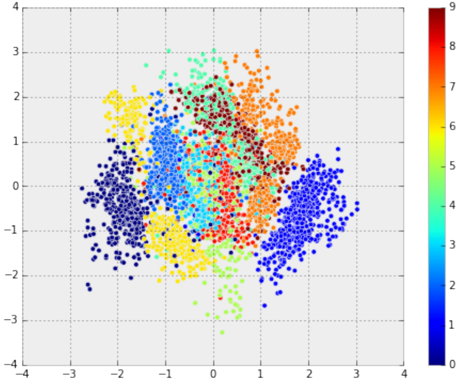
- How to find W_n, b_n?
- Define loss function $L(Y, \hat{Y})$ and use your favourite opt method.

Auto encoders example

Auto encoders example



Auto encoders example



http://dpkingma.com/sgvb_mnist_demo/demo.html

Stochastic Neighbor Embedding

Stochastic Neighbor Embedding

X – high dimensional obj and Y – low dimensional ones, σ – width params

Stochastic Neighbor Embedding

X – high dimensional obj and Y – low dimensional ones, σ – width params

$$p_{j|i} = \frac{\exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2/2\sigma_i^2)}{\sum_{k\neq i}\exp(-\|\mathbf{x}_i - \mathbf{x}_k\|^2/2\sigma_i^2)}$$

Stochastic Neighbor Embedding

X – high dimensional obj and Y – low dimensional ones, σ – width params

$$p_{j|i} = \frac{\exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2/2\sigma_i^2)}{\sum_{k \neq i} \exp(-\|\mathbf{x}_i - \mathbf{x}_k\|^2/2\sigma_i^2)} \quad q_{j|i} = \frac{(-\|\mathbf{y}_i - \mathbf{y}_j\|^2)}{\sum_{k \neq i}(-\|\mathbf{y}_i - \mathbf{y}_k\|^2)}$$

Stochastic Neighbor Embedding

X – high dimensional obj and Y – low dimensional ones, σ – width params

$$p_{j|i} = \frac{\exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2/2\sigma_i^2)}{\sum_{k\neq i}\exp(-\|\mathbf{x}_i - \mathbf{x}_k\|^2/2\sigma_i^2)} \quad q_{j|i} = \frac{(-\|\mathbf{y}_i - \mathbf{y}_j\|^2)}{\sum_{k\neq i}(-\|\mathbf{y}_i - \mathbf{y}_k\|^2)}$$

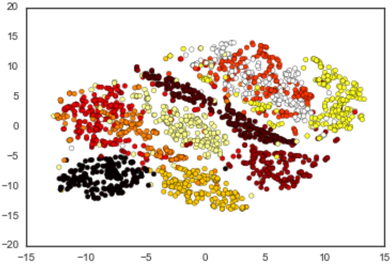
$$KL(P||Q) = \sum_j \sum_i p_{i|j} \log \frac{p_{i|j}}{q_{i|j}} \to \min_q$$

Stochastic Neighbor Embedding

X – high dimensional obj and Y – low dimensional ones, σ – width params

$$p_{j|i} = \frac{\exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2 / 2\sigma_i^2)}{\sum_{k \neq i} \exp(-\|\mathbf{x}_i - \mathbf{x}_k\|^2 / 2\sigma_i^2)} \quad q_{j|i} = \frac{(-\|\mathbf{y}_i - \mathbf{y}_j\|^2)}{\sum_{k \neq i} (-\|\mathbf{y}_i - \mathbf{y}_k\|^2)}$$

$$KL(P||Q) = \sum_j \sum_i p_{i|j} \log \frac{p_{i|j}}{q_{i|j}} \to \min_q$$

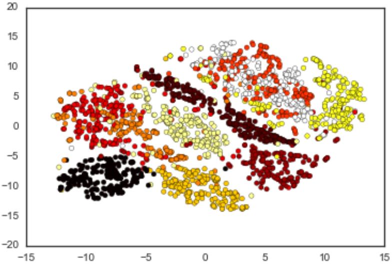


Stochastic Neighbor Embedding

X – high dimensional obj and Y – low dimensional ones, σ – width params

$$p_{j|i} = \frac{\exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2/2\sigma_i^2)}{\sum_{k\neq i}\exp(-\|\mathbf{x}_i - \mathbf{x}_k\|^2/2\sigma_i^2)} \quad q_{j|i} = \frac{(-\|\mathbf{y}_i - \mathbf{y}_j\|^2)}{\sum_{k\neq i}(-\|\mathbf{y}_i - \mathbf{y}_k\|^2)}$$

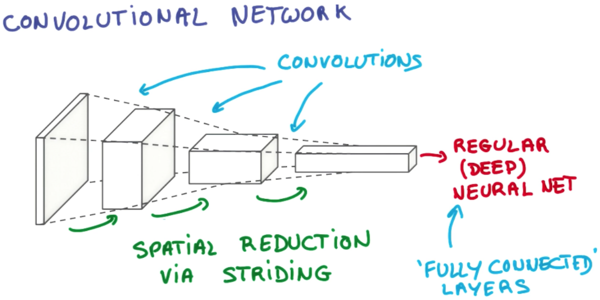
$$KL(P||Q) = \sum_j \sum_i p_{i|j} \log \frac{p_{i|j}}{q_{i|j}} \to \min_q$$



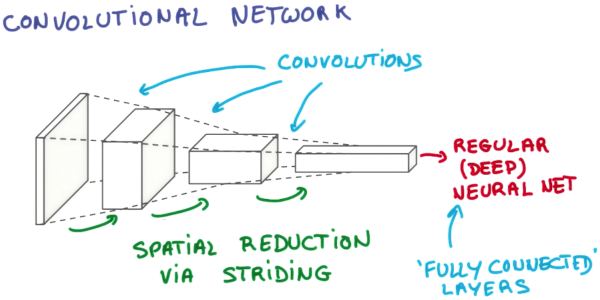
Deep Neural Nets + t-SNE (modification of SNE with Student distr):
http://cs.stanford.edu/people/karpathy/cnnembed/

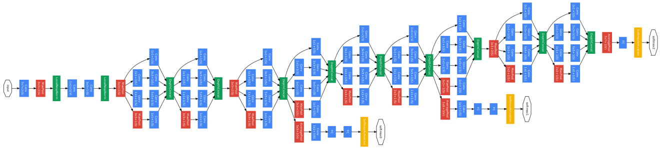
CNN

CNN


CONVOLUTIONAL NETWORK
CONVOLUTIONS
REGULAR (DEEP) NEURAL NET
SPATIAL REDUCTION VIA STRIDING
'FULLY CONNECTED' LAYERS

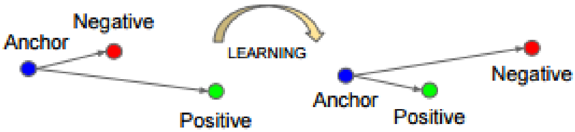
CNN


CONVOLUTIONAL NETWORK
CONVOLUTIONS
REGULAR (DEEP) NEURAL NET
SPATIAL REDUCTION VIA STRIDING
'FULLY CONNECTED' LAYERS

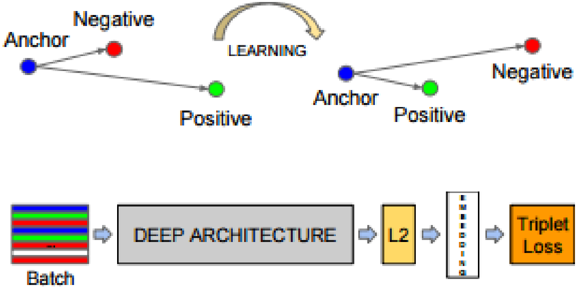


DNN Metric Learning Triplet Loss

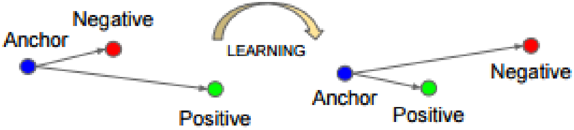
DNN Metric Learning Triplet Loss

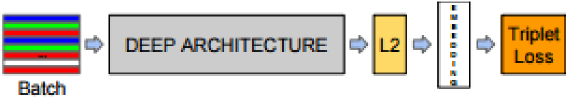


DNN Metric Learning Triplet Loss



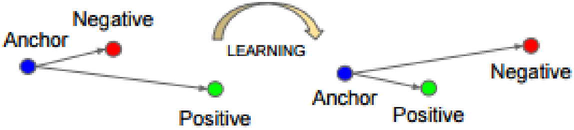
DNN Metric Learning Triplet Loss

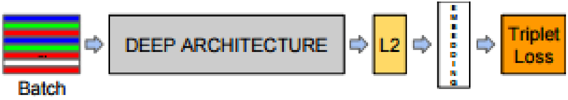




The loss that is being minimized is then

DNN Metric Learning Triplet Loss





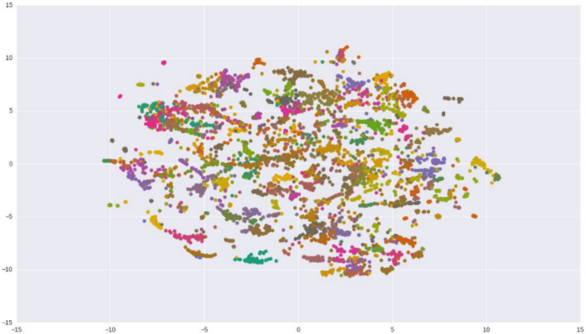
The loss that is being minimized is then

$$\sum_{i}^{N} \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \right]_+$$

DNN Metric Learning Triplet Face and Music

DNN Metric Learning Triplet Face and Music

DNN Metric Learning Triplet Face and Music



High level

High level

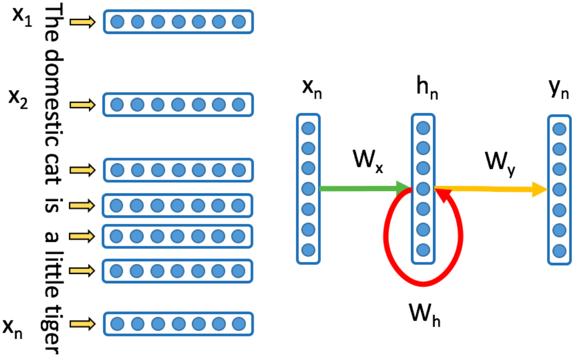
- We have mapped each object into vector

High level

- We have mapped each object into vector
- Let's train this vector for match complex object like words

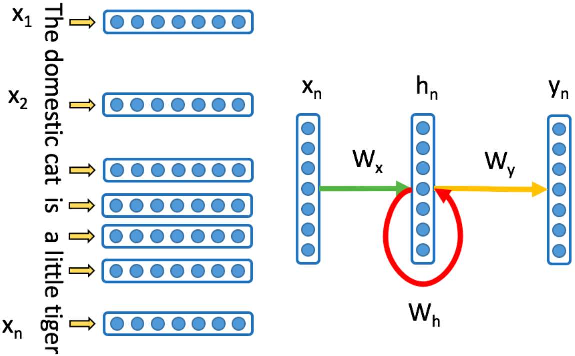
High level

- We have mapped each object into vector
- Let's train this vector for match complex object like words



High level

- We have mapped each object into vector
- Let's train this vector for match complex object like words



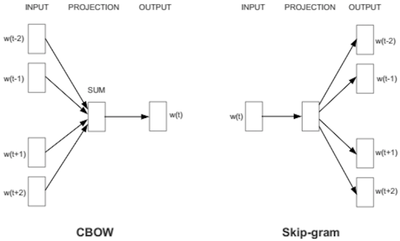
$$h_n = {\color{green}W_x} x_n + {\color{red}W_h} \sigma(h_{n-1})$$

$$y_n = \sigma({\color{orange}W_y} h_n)$$

Word2Vec

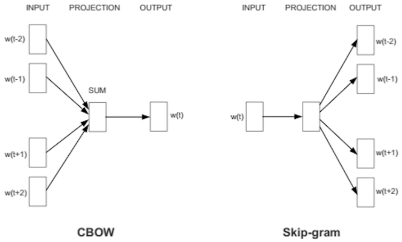
Word2Vec

- Shallow Neural Net



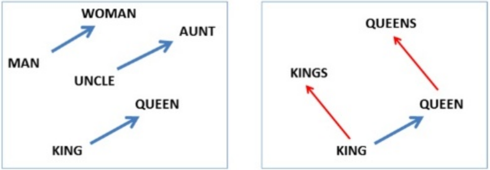
Word2Vec

- Shallow Neural Net



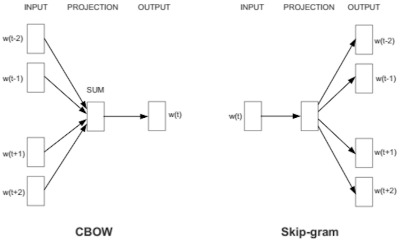
- Operations on embeddings are great

vec("man") – vec("king") + vec("woman") = vec("queen")



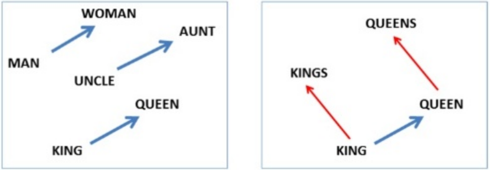
Word2Vec

- Shallow Neural Net



- Operations on embeddings are great

vec("man") – vec("king") + vec("woman") = vec("queen")



http://turbomaze.github.io/word2vecjson/

Image2Text

Image2Text

- Ok, we have a picture and want to represent in lower dim space

Image2Text

- Ok, we have a picture and want to represent in lower dim space
- Let's try to map picture to words sentence

Image2Text

- Ok, we have a picture and want to represent in lower dim space
- Let's try to map picture to words sentence

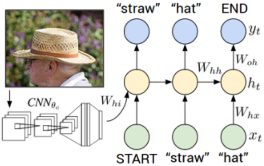
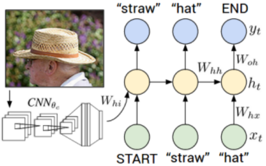


Image2Text

- Ok, we have a picture and want to represent in lower dim space
- Let's try to map picture to words sentence




man in black shirt is playing guitar.

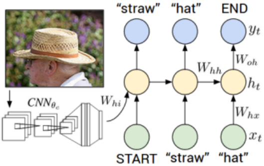

construction worker in orange safety vest is working on road.


two young girls are playing with lego toy.


boy is doing backflip on wakeboard.

Image2Text

- Ok, we have a picture and want to represent in lower dim space
- Let's try to map picture to words sentence



man in black shirt is playing guitar.

construction worker in orange safety vest is working on road.

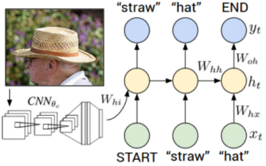
two young girls are playing with lego toy.

boy is doing backflip on wakeboard.

http://cs.stanford.edu/people/karpathy/deepimagesent/

Image2Text

- Ok, we have a picture and want to represent in lower dim space
- Let's try to map picture to words sentence




man in black shirt is playing guitar.


construction worker in orange safety vest is working on road.


two young girls are playing with lego toy.


boy is doing backflip on wakeboard.

http://cs.stanford.edu/people/karpathy/deepimagesent/
http://cs.stanford.edu/people/karpathy/deepimagesent/rankingdemo/

Generative Adversarial Networks

Generative Adversarial Networks

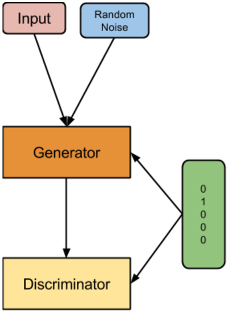
- Image Generation is a lintel bit hardcore

Generative Adversarial Networks

- Image Generation is a lintel bit hardcore
- Most modern idea is like this

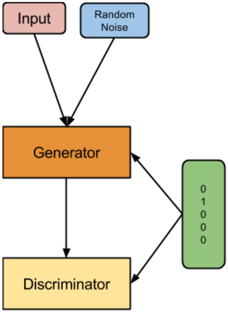
Generative Adversarial Networks

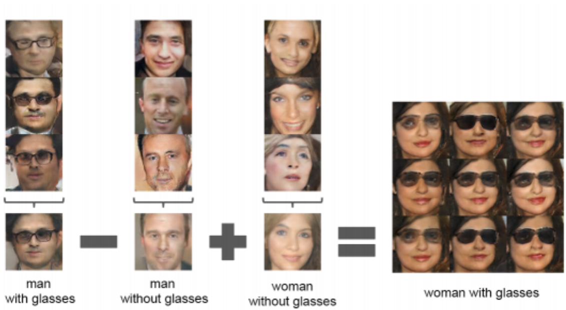
- Image Generation is a lintel bit hardcore
- Most modern idea is like this



Generative Adversarial Networks

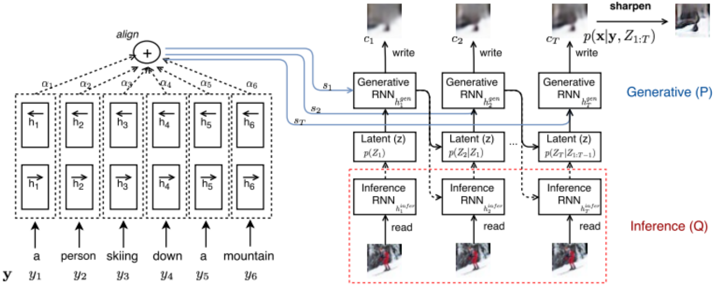
- Image Generation is a lintel bit hardcore
- Most modern idea is like this





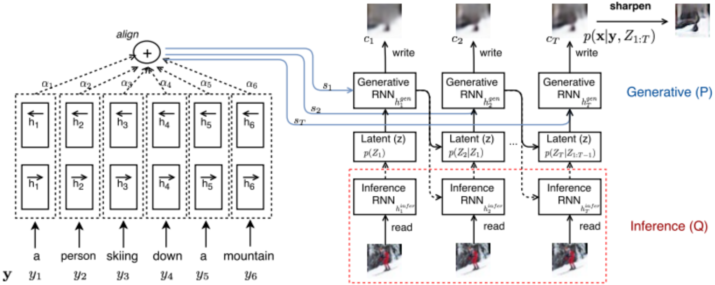
Text2Image

Text2Image



align
sharpen
$p(\mathbf{x}|\mathbf{y}, Z_{1:T})$
write
Generative RNN
Latent (z)
$p(Z_1)$
$p(Z_2|Z_1)$
$p(Z_T|Z_{1:T-1})$
Inference RNN
read
Generative (P)
Inference (Q)
a
person
skiing
down
a
mountain

Text2Image



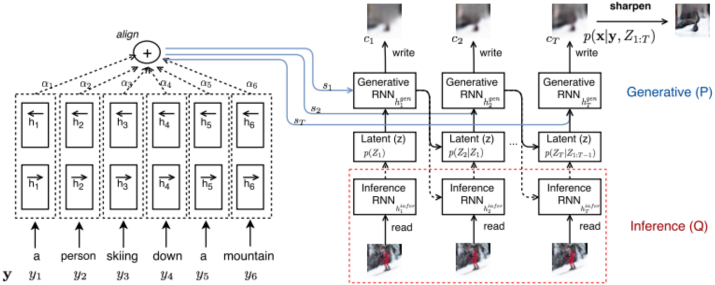
A stop sign is flying in blue skies.

A herd of elephants flying in the blue skies.

A toilet seat sits open in the grass field.

A person skiing on sand clad vast desert.

Text2Image



A stop sign is flying in blue skies.

A herd of elephants flying in the blue skies.

A toilet seat sits open in the grass field.

A person skiing on sand clad vast desert.

https://arxiv.org/pdf/1511.02793v2.pdf

End

Current Status of your Field!

Thanks for your attention!